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Handling Missing Data in Coverage Estimation, with Application to the 1986 Test of Adjustment Related Operations

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ABSTRACT

This paper discusses methods used to handle missing data in post-enumeration surveys for estimating census coverage error, as illustrated for the 1986 Test of Adjustment Related Operations (Diffendal 1988). The methods include imputation schemes based on hot-deck and logistic regression models as well as weighting adjustments. The sensitivity of undercount estimates from the 1986 test to variations in the imputation models is also explored.

KEY WORDS: Imputation; Nonresponse; Post-enumeration survey; Weighting adjustments; Undercount.

1. INTRODUCTION

Missing data can be a major source of uncertainty in the estimation of coverage error for the decennial censuses in the United States (Freedman and Navidi 1986; Fay, Passel, and Robinson 1988, Chapter 6). For both the 1960 and 1980 Decennial Censuses, several estimates of coverage error were computed under different treatments of the missing data.

The Bureau of the Census has conducted many tests of methods for coverage error estimation to prepare to handle missing data and other problems for the 1990 Decennial Census. One such test was the 1986 Test of Adjustment Related Operations (TARO) (Diffendal 1988), which used the 1986 Census of Central Los Angeles County. Changes in field methodology and design for TARO reduced the levels of certain types of missing data from the levels for 1980 (Hogan and Wolter 1988). Nevertheless, some missing-data problems remained.

This paper describes the missing-data problems in TARO and how they were handled in the estimation process. Section 2 gives a brief description of how coverage error was estimated in TARO. Sections 3-6 discuss the types of missing data that occurred, the extent to which they occurred, and the methods used to handle them. These methods include a weighting adjustment for unit nonresponse (noninterviews), hot-deck imputation for missing demographic and housing characteristics, and imputation using logistic regression models for certain binary items related to enumeration in the census. Section 7 presents coverage error estimates under alternative imputation models and alternative treatments of certain problem cases. The lowest and highest estimated undercount rates obtained using these alternatives are 8.50% and 10.16% for Hispanics, 5.86% and 7.81% for Asian non-Hispanics, and 5.81% and 6.59% for Others. The estimates from TARO for the three race categories were 9.85%, 7.32%, and 6.21%, respectively. A concluding discussion is given in Section 8.

2. ESTIMATING CENSUS COVERAGE ERROR

Diffendal (1988) discusses in detail how census coverage error was estimated in TARO. This section describes briefly those aspects necessary for understanding the rest of this paper.

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Coverage error was estimated using data from a post-enumeration survey (PES) of people in the census site. First a sample of blocks in the site was drawn. Then each housing unit in the sample blocks was surveyed to determine its occupants on Census Day, its occupants at the time of the PES and where they lived on Census Day, and the characteristics of the occupants.

Two samples were used to estimate census coverage error. The P (population) sample was composed of the people who lived in the PES sample blocks at the time of the PES. An attempt was made to match each P-sample person to a person enumerated in the census to determine whether the P-sample person had been enumerated; the match rate within each domain of study was used essentially to estimate the capture rate of the census for that domain. The E (enumeration) sample was composed of the people who were enumerated in the census as living in the PES sample blocks; this sample was used to estimate the number of erroneous enumerations (e.g., fictitious enumerations and duplicates) and unmatchable persons (e.g., persons for whom no names were reported) in the census within each domain. An attempt was made to match each E-sample person to a person in the PES. Each E-sample match was considered a correct enumeration since the PES indicated that the person should have been enumerated. Each E-sample nonmatch was followed up to determine whether it was an erroneous enumeration or a correct enumeration that was missed in the PES (which is not itself assumed to have perfect coverage).

If a PES of the entire United States were conducted, individuals in the P-sample who moved out of Central Los Angeles County between Census Day and the PES would be interviewed in the PES. An attempt to match these individuals to census enumerations in Central Los Angeles County would be made, and the resulting data would be used in the estimation of coverage error for Central Los Angeles County. Similarly, individuals in the P-sample who moved into Central Los Angeles County between Census Day and the PES would contribute to coverage error estimates outside of Central Los Angeles County. However, because the census and PES for TARO were conducted only in Central Los Angeles County and not in the entire United States, outmovers from the test site were not interviewed in the PES and inmovers did not apply to the test. Thus data for inmovers and outmovers were not used in the estimation. (Note that data for movers *within* test site were used, however). This issue is discussed further in Section 7.2.

The "dual-system" estimator of the population size (see Marks, Seltzer, and Krotki 1974, Krotki 1978, and Wolter 1986 for discussion and references) is written

$$\text{DSE} = N_p\,(\text{CEN-SUB-EE})/\text{M}, \tag{1}$$

where N_p is the weighted number of people in the P-sample, CEN is the unadjusted census count, SUB is the number of whole-person substitutions (for unit nonresponse) in the census, EE is a weighted estimate of the number of erroneous enumerations and unmatchable persons in the census, and M is the weighted number of matches between the P-sample and census; census data provide CEN and SUB, whereas P- and E-sample data provide N_p, EE, and M. The dual-system estimator can be thought of as inflating the estimated number of correct and matchable census enumerations (CEN-SUB-EE) by the inverse of the estimated census capture rate (M/N_p).

The theory of dual-system estimation assumes that for both the census and the PES, the probability of capture is constant across all people in the domain to which the estimator is applied (Wolter 1986). Thus no one group of people in the domain should be more or less likely to be enumerated in the census or PES than any other group. To make this assumption more realistic in TARO, separate dual-system estimates were computed within poststrata based on person and housing characteristics. The poststrata are described in Diffendal (1988). One example is the Hispanic male renters of ages 30 to 44 living in primarily Hispanic blocks.

To summarize, the P- and E-sample data needed for coverage error estimation were the match status (match vs. nonmatch) for each P-sample person, the enumeration status (correct vs. erroneous) for each E-sample person, and person and housing characteristics for each person in both samples.

3. P-SAMPLE HOUSEHOLD NONINTERVIEWS

Occasionally, a PES interviewer was unable to obtain an interview for an occupied housing unit; this occurred, for example, when the occupants refused to respond. Of the 5,935 housing units that were judged to be nonvacant, 32 (0.5%) were classified as having household noninterviews. The occurrence of household noninterviews resulted in missing data on the number of people in each household, person and housing characteristics, and match statuses.

The block-sample design of the PES afforded a simple way to handle P-sample household noninterviews. Within each sample block, the sampling weights of the noninterview households were redistributed across the interviewed households. The noninterview weighting adjustment basically assumes that the distributions of people, characteristics, and match statuses for households not interviewed within a block are the same as for households interviewed. This assumption was used because households tend to be more similar within blocks than across blocks, although noninterview households still probably differ somewhat from interviewed households, especially with respect to household size (see, e.g., Palmer 1967).

It is possible that the data obtained for a household by proxy interview (which in TARO referred to a completed interview with someone outside the household) are of sufficiently low quality that such a household should be classified as a noninterview household. The quality of data from the 189 proxy interviews in TARO is discussed in Section 4, and some coverage error estimates with proxy interviews treated as noninterviews are presented in Section 7.

4. MISSING CHARACTERISTICS IN THE P- AND E-SAMPLES

Even when an interview was obtained for a P-sample household, the data on person and housing characteristics were sometimes incomplete. Incomplete data on characteristics also occurred in the census and therefore in the E-sample.

The variables used in poststratification for TARO (Diffendal 1988) included the housing variable Tenure (1 = owned, 2 = rented or occupied without payment) and the person variables Sex (1 = male, 2 = female), Age (1 = 0-14, 2 = 15-29, 3 = 30-44, 4 = 45-64, 5 = 65+), and Race (1 = Hispanic, 2 = Asian non-Hispanic, 3 = Other). In addition, the housing variable Structure (1 = single-unit, 2 = multiunit) was used in handling missing P-sample match statuses and missing E-sample enumeration statuses (see Sections 5 and 6).

Table 1 displays the missing-characteristic counts for the entire P- and E-samples and for cases coming from P-sample proxy interviews. For the P- and E-samples, the highest missing-data rate was 7.0% for E-sample Race, with all other rates being 3.5% or lower. The missing-data rates for P-sample proxy cases were all several times higher than those for the entire P-sample, although only Tenure (20.2%) had a rate higher than 10%.

Missing characteristics for each of the samples (P and E) were imputed by a hot-deck method involving two passes through the data after the data had been sorted geographically. On the first pass, missing values of Tenure, Structure, and Race were imputed using the most

Table 1

Missing-Characteristic Counts (% in Parentheses)
for the Entire P- and E-Samples and for P-Sample Proxy Interviews

Variable	P-Sample (19,552 persons)	E-Sample (20,976 persons)	P-Sample Proxy (430 persons)
Tenure	690 (3.5)	154 (0.7)	87 (20.2)
Structure	459 (2.3)	343 (1.6)	38 (8.8)
Sex	418 (2.1)	82 (0.4)	18 (4.2)
Age	137 (0.7)	432 (2.1)	18 (4.2)
Race	155 (0.8)	1463 (7.0)	17 (4.0)

NOTE: The 19,552 persons in the P-sample include the 430 proxy cases.

recent observed data, because of the presumed strong relation between these variables and geography. In addition, distributions of Sex and Age were tabulated for categories of type of household (single-person vs. multiperson), marital status, relationship to head of household, and sex and age of head of household, using all observed data. On the second pass, missing values of Sex and Age were imputed at random from the distributions tabulated during the first pass. Further details on the imputation of characteristics in TARO can be found in Schenker (1987).

In summary, the block sample design of the PES was helpful not only in developing a noninterview weighting scheme (Section 3), but also in the imputation of characteristics that tend to be clustered by block, that is, Tenure, Structure, and Race.

5. MISSING MATCH STATUSES IN THE P-SAMPLE

Of the 19,552 P-sample cases resulting from completed interviews, 161 (0.8%) were missing match statuses for dual-system estimation. All but three of these unresolved cases fell into two broad categories: 105 cases for which matching was not attempted due to incomplete names and/or insufficient characteristics; and 53 movers between Census Day and the PES for whom there were problems specifying a Census Day address or finding the census questionnaire for the Census Day address.

A traditional approach to handling a missing binary item such as match status is to impute one of the two possible outcomes for the missing item. For example, in the estimation of undercount for the 1980 Decennial Census, the match status for each unresolved P-sample case was imputed from a resolved case with similar characteristics (Fay, Passel, and Robinson 1988, Chapter 6). A different approach was taken in TARO, however. After all missing characteristics were imputed using the methods described in Section 4, a match probability was imputed for each unknown match status; the probability was estimated using an explicit model (to be described later in this section). The contribution of the unresolved cases to the M term of the dual-system estimate (1) was the weighted sum of the imputed probabilities.

Probabilities rather than binary outcomes were imputed for two reasons. First, imputing random binary outcomes is less efficient than imputing estimated probabilities, yielding estimates with higher variances (see Rubin 1987, p. 15). Second, because imputed probabilities represent uncertainty about the missing match statuses, it should be possible to use the probabilities to obtain a variance due to imputation. Note, however, that since the dual-system estimator (1) is nonlinear in M, imputing a probability (or mean) for each missing binary outcome introduces some bias into the estimation (see Rubin 1987, p. 14). Current research is investigating the use of imputed probabilities for missing binary data.

The following logistic regression approach was used to impute match probabilities. Let X denote a vector of predictors, Y = match or nonmatch, and $p = \Pr(Y = \text{match} \mid X)$. The parameter vector β of the logistic regression model

$$\text{logit}(p) = \log[p/(1-p)] = X'\beta$$

was estimated from the data for the resolved cases using the Bayesian techniques for categorical logistic regressions described in Rubin and Schenker (1987); these techniques involve adding fractional observations to each cell in the logistic regression and then fitting the model by standard maximum-likelihood methods. Then for unresolved case j, with $X = x_j$, the imputed match probability was

$$\hat{p}_j = \text{logit}^{-1}(x_j'\hat{\beta}) = \exp(x_j'\hat{\beta}) / [1 + \exp(x_j'\hat{\beta})],$$

where $\hat{\beta}$ denotes the estimate of β. The background variables used to define X were Tenure, Structure, Sex, Age, and Race, as well as variables indicating regular interview versus proxy interview and mover versus nonmover between Census Day and the PES.

Table A1 (in the Appendix) gives the logistic regression coefficient estimates. The large coefficients associated with interview and mover status indicate that proxy and mover cases have much lower imputed match probabilities than others. It may be that these lower match probabilities are due in part to difficulties in matching proxy and mover cases rather than just lower census capture rates for these cases. If this is true, alternative treatments of the data may be in order; such alternatives are considered in Section 7.

Of the 19,391 resolved P-sample cases, 17,018 (87.8%) were matches. The (unweighted) sum of the 161 imputed match probabilities was 124.66; thus the imputed match rate was 77.4%. Although a stratified sample of blocks was used in TARO, the estimation of the logistic regression parameters assumed a simple random sample of people. To examine the possible biases due to not accounting for the stratification, the logistic regression was fitted again (after TARO was completed) with indicator variables for the six sampling strata (Diffendal 1988) included in X. The result of this refinement is a sum of imputed match probabilities equal to 124.50 (77.3%). The minor effect of this change on estimates of census coverage error is demonstrated in Section 7. Implications of possible design effects due to clustering are discussed in Section 8.

6. MISSING ENUMERATION STATUSES IN THE E-SAMPLE

Of the 20,976 cases in the E-sample, 3,714 were followed up or should have been followed up. After followup, 979 cases (4.7% of total, 26.4% of followup) had missing enumeration statuses. All but nine of these unresolved cases fell into four broad categories: 498 cases that should have been followed up but were not; 257 cases in which the respondent to the followup interview did not know the person in question; 137 cases for which the interview yielded insufficient information to determine an enumeration status; and 78 cases for which there were followup noninterviews.

Missing enumeration statuses in the E-sample were handled by imputing a probability of erroneous enumeration for each unresolved case. The contribution of the unresolved cases to the EE term of the dual-system estimate (1) was the weighted sum of the imputed probabilities. The imputation procedure was analogous to that used for P-sample match statuses with one major change: Since missing enumeration statuses resulted solely from followup, only the resolved cases from followup were used in estimating the logistic regression. The background variables used to define X for the logistic regression were Tenure, Structure, Sex, Age, and Race, along with variables indicating whether the census questionnaire for the person's household was returned by mail and whether the entire household or only part of the household was not matched before followup. Table A2 (in the Appendix) gives the logistic regression coefficient estimates.

Of the 17,262 non-followup cases, 278 (1.6%) were classified as erroneous enumerations or unmatchable. There were 2,735 resolved followup cases, of which 82 (3.0%) were classified as erroneous enumerations. The (unweighted) sum of the 979 imputed probabilities was 21.93 (2.2%). When indicator variables for the sampling strata are included in X, the sum changes to 23.58 (2.4%). As with the P-sample, this change has a very minor effect on estimates of coverage error; see Section 7.

7. ESTIMATES OF COVERAGE ERROR UNDER ALTERNATIVE TREATMENTS OF MISSING DATA AND OTHER PROBLEM CASES

This section examines the effects of alternative treatments of missing data and other problem cases on estimates of coverage error for the three categories of race defined by the variable Race (Hispanic, Asian non-Hispanic, and Other). For a given treatment and race category, let $\hat{N}$ be the sum of the dual-system estimates over all poststrata corresponding to the race category and let N_c be the sum of the unadjusted census counts over the poststrata. The estimated undercount rate is then $100(1 - N_c/\hat{N})\%$.

Consider first the alternative of including indicators of the sampling strata as predictors in the P- and E-sample logistic regressions for imputing match and erroneous enumeration probabilities, as discussed in Sections 5 and 6. The estimated undercount rates from TARO, which were obtained without using these predictors, are 9.85% for Hispanics, 7.32% for Asian non-Hispanics, and 6.24% for Others. When indicators of the sampling strata are used, the estimates change to 9.82% for Hispanics, 7.31% for Asian non-Hispanics, and 6.21% for Others. The largest difference due to including the sampling stratum indicators is only 0.03%. For all the alternative treatments to be considered, however, this refinement is used because it is in principle more correct; for instance, it should yield more accurate standard errors.

7.1 Treatments that Lower the Estimated Undercount

The match rate for the 375 resolved P-sample proxy cases was 78.9% as opposed to the overall P-sample rate of 87.8%. While it may be true that proxy cases were actually captured in the census less frequently than others, it is possible that part of the difference in the match rates is due to missing and/or incorrect proxy data (see Section 4). A conservative treatment would be to classify the 189 proxy interviews as household noninterviews and apply the weighting adjustment described in Section 3; this would essentially assign proxy cases the same match rate as nonproxy cases. (Note that when all proxy interviews are classified as noninterviews, an indicator of proxy/nonproxy status is no longer included in the logistic regression model for imputing match probabilities).

The match rate for the 277 resolved P-sample movers (between Census Day and the PES) was 66.1%. It is generally believed that movers are captured in the census at a lower rate than nonmovers, but it may be that the low match rate for movers is partly due to difficulties inherent in matching movers, such as problems in obtaining a correct Census Day address. A conservative

Table 2

Estimated Undercount Rates (in %) by Race Under Alternative Treatments of P-sample Proxy Interviews, P-sample Movers, and E-sample W1's

Treatment (1 = alternative, 0 = TARO)			Hispanic	Asian non-Hispanic	Other
Proxy	Mover	W1			
0	0	0	9.82	7.31	6.21
0	0	1	9.30	6.76	5.83
0	1	0	9.33	7.24	6.19
0	1	1	8.80	6.69	5.81
1	0	0	9.55	6.52	6.24
1	0	1	9.03	5.96	5.86
1	1	0	9.04	6.45	6.22
1	1	1	8.51	5.90	5.84

NOTE: Indicators of the sampling strata were used as predictors in the logistic regressions for imputing match and erroneous enumeration probabilities.

treatment would be to classify all cases for movers as unresolved and then impute match probabilities for unresolved cases using a logistic regression model that does not include mover/nonmover status as a predictor. This would essentially assign movers the same match rate as nonmovers.

Of the 979 unresolved E-sample cases, 257 had the followup interview code W1, meaning that the respondent did not know the person in question. A code of W1 could have indicated that the person in question was fictitious. Therefore, after TARO, all W1's were reviewed by experienced matching personnel. Any case that showed evidence (such as a note from the interviewer) of possibly being fictitious was marked; there were 118 such cases. An alternative treatment to that used in TARO would be to classify the 118 cases as resolved erroneous enumerations before imputation. This would raise both the observed and imputed rates of erroneous enumeration.

Table 2 displays the undercount estimates by race category for the 2x2x2 factorial design with the factors being whether or not alternative treatments are used for proxy interviews, movers, and W1's. The ranges between the lowest and highest estimated undercount rates are 1.31% for Hispanics, 1.41% for Asian non-Hispanics, and 0.43% for Others.

Note that for each race category, there is not much interaction between the treatments of proxy interviews, movers, and W1's. In fact, the following simple additive model can be used to predict the entries in Table 2 for each race category:

$$\hat{Y} = \hat{\alpha}_0 + I_p\hat{\alpha}_p + I_m\hat{\alpha}_m + I_w\hat{\alpha}_w, \tag{2}$$

where $\hat{Y}$ is the predicted estimate of the undercount rate, I_p, I_m, and I_w are the treatmeant indicators (1 = alternative, 0 = TARO) for proxy interviews, movers, and W1's, respectively, and $\hat{\alpha}_0$, $\hat{\alpha}_p$, $\hat{\alpha}_m$, and $\hat{\alpha}_w$, are parameter estimates given in Table 3. The parameter α_0 is the estimated undercount rate when no alternative treatments are used; α_p, α_m, and α_w are the effects of using alternative treatments for proxy interviews, movers, and W1's, respectively. The largest residual when equation (2) is used to predict the entries in Table 2 is 0.02%.

Table 3

Parameter Estimates for the Additive Model (2) for Predicting the Estimated Undercount Rates in Table 2

	Hispanic	Asian non-Hispanic	Other
$\hat{\alpha}_o$	9.82	7.31	6.21
$\hat{\alpha}_p$	−0.28	−0.7925	0.03
$\hat{\alpha}_m$	−0.505	−0.0675	−0.02
$\hat{\alpha}_w$	−0.525	−0.5525	−0.38

7.2 A Procedure that Raises the Estimated Undercount

Because TARO was confined to one small area in the United States, no PES data could be obtained for people who moved out of the test site between Census Day and the PES. The omission of these outmovers from estimation was equivalent to assuming that they had the same capture rate in the census as the included cases. This was a conversative assumption, since movers are generally believed to have a lower capture rate than nonmovers.

There were 409 people who moved into the test site between Census Day and the PES. These inmovers were not included in the estimation because their Census Day addresses were outside the test site and thus their data applies to other areas. Moreover, there were no census cases to which to match the inmovers since they were outside the test site on Census Day.

A procedure that might indicate the effect of including outmovers in the estimation would be to include the 409 inmovers as substitutes and impute match probabilities for them (since their match statuses are unknown). The treatments yielding the highest and lowest estimates in Table 2 have been applied to the TARO data with inmovers included; the results are displayed in Table 4. Note that the lower estimated undercount rates in Table 4 (obtained using the alternatives to the TARO treatments for proxy interviews, movers, and W1's) are all within 0.04% of the corresponding estimates in Table 2. This result is expected, since the addition of cases having an imputed match rate that is approximately the same as the overall match rate should not affect the estimates much. The higher estimates in Table 4 are larger than the corresponding estimates in Table 2 by 0.34% for Hispanics, 0.50% for Asian non-Hispanics, and 0.38% for Others.

Table 4

Estimated Undercount Rates (in %) by Race When Inmovers are Included in the Data with Imputed Match Probabilities

Treatment (1 = alternative, 0 = TARO)			Hispanic	Asian non-Hispanic	Other
Proxy	Mover	W1			
0	0	0	10.16	7.81	6.59
1	1	1	8.50	5.86	5.81

NOTE: Indicators of the sampling strata were used as predictors in the logistic regressions for imputing match and erroneous enumeration probabilities.

8. SUMMARY AND DISCUSSION

A combination of weighting and (random and nonrandom) imputation methods was used to handle missing data in TARO. P-sample household noninterviews were handled by a block-level weighting adjustment. A hot-deck imputation method was used for missing characteristics in both samples. Missing P-sample match statuses and E-sample enumeration statuses were handled using imputed probabilities estimated by logistic regression methods.

As mentioned in Sections 5 and 6, the use of imputed probabilities for missing P-sample match statuses and E-sample enumeration statuses should facilitate the assessment of variability due to imputing these statuses. To assess this variability completely, it is necessary to measure variability due to estimating the logistic regression parameters as well as the variability due to imputation given β (Rubin and Schenker 1986). Thus an estimated variance-covariance matrix for $\hat{\beta}$ is needed. Since a cluster sample was used in TARO, the logistic regression estimation procedures (Section 5), which assume a simple random sample, do not provide an accurate estimate of the variance-covariance matrix. This was not a major concern in TARO, because the measurement of imputation variance was not a primary goal. Moreover, for the nonresponse rates achieved in TARO, the variability due to uncertainty in estimating β is likely to be minor relative to the uncertainty due to imputation given β (Rubin and Schenker 1986).

Although it is possible in principle to assess the variability due to imputing match and enumeration statuses using the TARO procedures, variability due to imputing missing characteristics (Section 4) cannot be quantified. One way to make the quantification of such variability possible would be to multiply impute characteristics in the P- and E-samples (Rubin 1987). Several dual-system estimates would then need to be calculated, however — one for each set of imputations.

The models underlying the weighting and imputation methods used in TARO assume that given the observed data, the chance of a variable being missing does not depend on its value. Another issue regarding imputation is how best to impute characteristics and match statuses (or enumeration statuses) simultaneously. The TARO procedure of first imputing characteristics and then imputing statuses conditional on the imputed characteristics assumes that statuses are not useful predictors for imputing characteristics. Models that relax the TARO assumptions may be more appropriate. Rubin, Schafer, and Schenker (1988) discuss this further.

Missing data are only one source of error in estimating coverage. Other sources, such as matching error and violations of the assumption of constant capture probabilities (Section 2), are discussed in Hogan and Wolter (1988). After assessing all of these sources of error for TARO, Hogan and Wolter conclude that the TARO coverage measurement is more accurate than the original enumeration.

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APPENDIX

LOGISTIC REGRESSION RESULTS

Table A1

Results for P-Sample Logistic Regression

Predictor	Codes	Estimated Coefficient
Intercept		1.47
Interview Status	1 if regular, −1 if proxy	.36
Mover Status	1 if nonmover, −1 if mover	.60
Tenure	1 if owner, −1 otherwise	.46
Structure	1 if single-unit, −1 if multiunit	−.16
Sex	1 if male, −1 if female	−.09
Age 1	1 if 0-14, −1 if 65+, 0 otherwise	−.06
Age 2	1 if 15-29, −1 if 65+, 0 otherwise	−.46
Age 3	1 if 30-44, −1 if 65+, 0 otherwise	−.02
Age 4	1 if 45-59, −1 if 65+, 0 otherwise	.13
Race 1	1 if Hispanic, −1 if Other, 0 if Asian non-Hispanic	−.14
Race 2	1 if Asian non-Hispanic, −1 if Other, 0 if Hispanic	.11

Table A2

Results for E-Sample Logistic Regression

Predictor	Codes	Estimated Coefficient
Intercept		−3.45
Questionnaire Status	1 if mail-return, −1 otherwise	.01
Pre-followup Status	1 if partial-household match, −1 if whole-household nonmatch	−.20
Tenure	1 if owner, −1 otherwise	.36
Structure	1 if single-unit, −1 if multiunit	.17
Sex	1 if male, −1 if female	.08
Age 1	1 if 0-14, −1 if 65+, 0 otherwise	−.30
Age 2	1 if 15-29, −1 if 65+, 0 otherwise	−.04
Age 3	1 if 30-44, −1 if 65+, 0 otherwise	−.34
Age 4	1 if 45-59, −1 if 65+, 0 otherwise	.10
Race 1	1 if Hispanic, −1 if Other, 0 if Asian non-Hispanic	−.02
Race 2	1 if Asian non-Hispanic, −1 if Other, 0 if Hispanic	−.38

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